A Survey of Shape Optimization of pneumatic Soft Robots/Actuators

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***Abstract*— in recent years soft pneumatic and fluid actuators have become a new, versatile way of movement in e.g robots. Generally coming up with a good design of these types of actuators have proven difficult, therefore a type of generative design method is often used in order to optimize the shape, to make the actuator more useful. This survey presents a few different approaches to make these actuators. And concludes with a summary of the problems/ benefits of using the different optimization techniques for automatically designing soft robots and actuators.**

I. INTRODUCTION

Soft robotic actuators have been proven to be very versatile, with many degrees of freedom, at a low cost. They have the ability to enter unreachable places, both in terms of form, where people or traditional robots may not fit , but also in terms of environment, being able to both move on land as well as in water. The latter may prove desirable in war, or when exploring the solar system. Other than this soft robots have already been proposed for chemists[4], to avoid getting in contact with dangerous contaminants. Further it has been thought that soft robots may be beneficial in the future of surgery[5] [8], where it possibly can offer less invasive alternative to traditional surgery, due to it being able move about in a way traditional robots nor humans can do. However these approaches often requires a lot of trial and error, knowing how a soft-robot/actuator moves is immensely difficult. Therefore there are a lot of ways people have tried to optimize the design and movement of these kinds of robots. One can use traditional analytical approaches, creating a model of how you want the robot to move. Or you can use a evolutionary approach - let the computer calculate the most optimal solution to the problem. And there may be even more ways to solve the design problem of these kinds of robots/actuators.

Thus we will explore in this survey the researchers ability to optimize the shape their creation in order to make it perform its task in an even better way. Going over the approaches currently in use, how they have worked out, and the benefits and problems with each of the different ways of solving the problem of shape optimization of soft robots and soft actuators.

II. Overview of Different optimization Approaches for the Design Problem

A. *Genetic Algorithms (GA)*

A genetic algorithm is what generally is being used as an optimization strategy. By borrowing the evolutionary approach of specimens and natural selection in accordance with a fitness-value. It has performed well on the problem of designing soft robotic actuators.

In their paper on automatic design of soft robots[1] J.Hiller and H.lipson found that, using a GA on tweaking the genome consisting of a list of vertices each containing 6 values(a representation of the X Y and Z coordinates, as well as density, falloff distance and material index). Then running this through a genetic algorithm crossing over half of each parent in each generation, using a mutation-rate of 20% with a certain chance of either removing a vertex, adding one, or just changing some values in a preexisting vertex.

The fitness of the system was determined to be the amount of positive length moved in the X direction. Then after running the algorithm/simulation a couple of days reached the solutions shown in figure 1, after a randomly initialized structure.

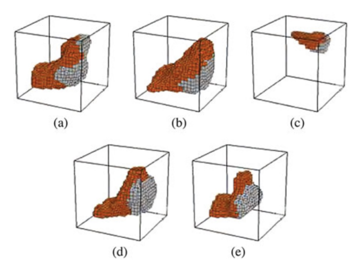

Fig. 1. Solutions from running the algorithm for "a couple of days"[1]

As they point out, there is a clear way that the algorithm prioritizes the optimization, they may have reached a global optimum. They chose to 3D-print one of the solutions. Doing this they found their simulation to be quite accurate to the real world. yielding the results in Figure 3.

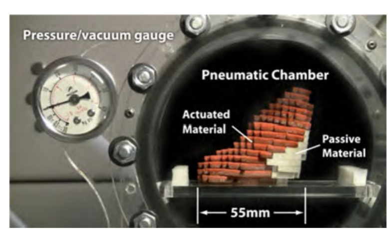

Fig. 2. The printed Solution B[1]

Further, Gundala et.al., showed in 2017 a GA optimized soft actuator[3]. They used a pre-made framework consisting of a MatLab-function for the GA, and ABACUS for the FEM (Finite Element Method)-simulation, in order to optimize the

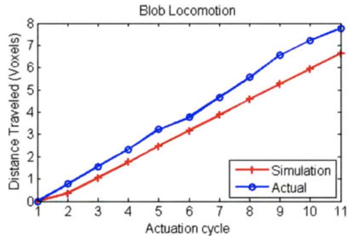

Fig. 3. Reality gap between the simulation and the real world[1]

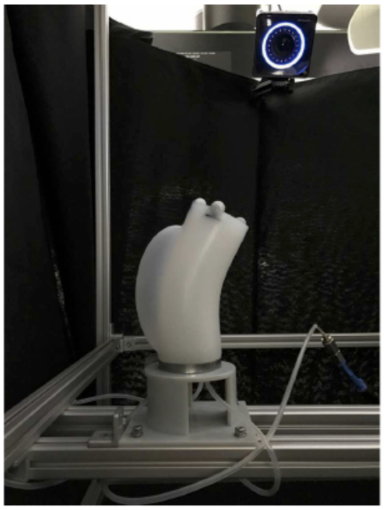

Fig. 4. The soft-actuator in need of optimization[3]

soft actuator in figure 4. They set the goal of the simulation to minimize the radius of curvature, whilst keeping the ballooning of the chamber as small as possible. It did this by adjusting the inner chamber, both position and thickness. Thus making the actuator move in a round motion when air is applied to the chamber. The GA, also here showed much potential, in optimizing the actuator.

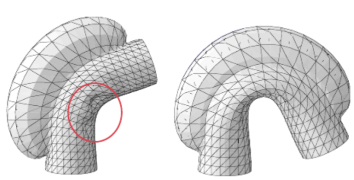

Fig. 5. The best specimen in the first generation versus the best specimen in the last[3]

This proves the approach of making soft robots, for a specific criteria, using GAs is quite possible, and may yield even more possibilities as computational power increases in the future, enabling even more sophisticated and higher resolution simulations. With even more tweak-able parameters, there is no seeing how far we could go.

Moreover Hiller and Lipson previously to prototyping the soft robot, made a simulator based on evolution to generate moving soft-robots[2]. Here they, instead of just using a genome of X, Y, and Z coordinates in addition to a few other parameters as they chose to do later on, they made the genome all the values of a neural net creating sinusoidal functions to make the finished robots have a more smooth appearance. Then they were able to create blobs that cohered well with the initial criteria.

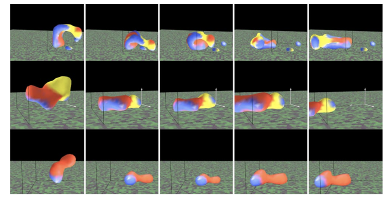

Fig. 6. evolved blobs in simulator[1]

Furthermore in their work on Growing and evolving soft robots[9], J. Rieffel et. al. managed to use GAs to evolve a genome consisting of a tetrahedron modifying the sizes between each of the vertices in each specimen. Then evolving the best gait for the given genome. Doing this in succession gave a robot that moved in a better way than just doing the optimization on one of the parameters.

GAs have given us quite good results for the time being and there are still lots more experiments to undertake using this technology. However the GA may only reach local optimums to a solution, and also may exploit a loopholes in the simulation, so one needs to be aware of this when one does use this approach.

B. Artificial Neural Networks(ANN)

ANNs - another biologically inspired method for solving optimization-problems, has - especially in the latter years become the go to way of applying machine learning, mostly it has been used in image, text and sound analysis, but as these are inherently just very complex optimization problems themselves. Such a method therefore is also viable for topology/shape optimization.

A Neural net mimics the neural synapses in the brain, by updating a set of layered nodes, given an input, and in time the network will learn that a given input will spike a given output.

Especially deep reinforcement learning[6] can potentially be even better than GAs, especially in terms of multi objective optimization of soft robots, making one robot useful doing several different tasks, such as both navigating on land and in water, this requires a lot of different move-sets, which a GA may have difficulty optimizing towards. Therefore for the future of shape-optimizing soft robots, deep reinforcement learning may prove a game-changer with regards to increased complexity.

C. Analytical approach

On their work on fiber reinforced soft fluid actuators[7] F. Connolly et. al found that, creating a model based on a cylindrical structure, consisting of several segments they were able to model complex movement by adjusting the angle and separation between the fibers in the mesh, thus making the actuator move in different and complex ways. In this paper they chose to model and create a human finger, and thumb, using this analytical model, yielding quite promising results.

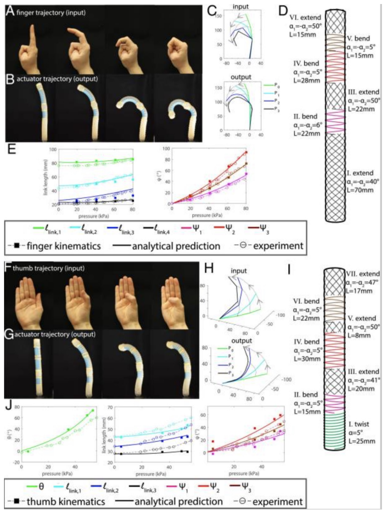

Fig. 7. F. Connolly et. al. model and created human finger and thumb[7]

As one can see from this solution, an analytical approach to this problem may also lead to very good and perhaps better solutions than just feeding coordinates into a GA or ANN. However reading the article, one does need a lot of empirical data, and knowhow of the technology in order to make something functional.

D. Benefits and problems with the different approaches

Benefits	
GA	• May reveal unconventional solutions to the problem • Easily tweaked in order to create a new robot/actuator for another problem
ANN	• May prove more useful as these kinds of robots may need more than one feature in the future
Analytical	• Gives a highly optimized result.

Problems	
GA	• Local search may(will) reveal a non-optimal solution • May evolve something that exploits a problem in the simulator
ANN	• Not properly tested for this problem •May prove to be superfluous, not a complex enough issue
Analytical	• Needs lots of previously gathered information on what problem to solve • For every new design a new analytical method needs to be developed • Difficult to make

E. Abbreviations and Acronyms

FEM - Finite Element Method
GA - Genetic Algorithm
ANN - Artificial Neural Network

III. CONCLUSIONS

In this paper i have layed out 4 ways of performing automated design of soft robotic actuators, using both local search techniques, and a more analytical way of optimizing the soft structure. They both perform quite good on the structures they wanted to create, however with vastly different forms and functions. Doing it analytically gave a drastically more optimized and complex result, being able to make a somewhat functioning human finger, rather than a blob moving in the X- direction as the GA was able to do. But as the analytical method is only able to modify an existing cylinder by modifying the mesh on the outside, the GA is able to make exactly what it wants, and may be able, in the future, to create almost anything, whereas the analytical model is unable to create more than a folding cylinder.

Comparing the GA and the ANN is quite difficult as the ANN/deep reinforcement learning optimization is still in its infancy. These approaches are still in essence quite similar - tweaking all the parameters it is given until it reaches a optimal result. In recent years Deep reinforcement learning has proved to be able to solve more complex problems than GAs ever could, especially with optimizing a lot of different variables, therefore for future, even more complex soft robots, could be created using deep neural networks.

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